Microfinance as a socially responsible investment

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Chapter 4

Social investment in microfinance: the trade-off between risk, return and outreach to the poor

4.1 Introduction

Access to finance is a crucial mechanism for generating persistent economic growth and for reducing world-wide poverty. Although data on access to financial services is still limited, it is clear that there is a huge unmet demand for financial services by the poor. Beck et al. (2007), for instance, estimate that about 40 to 80 percent of the populations in developing economies lack access to the formal banking sector. The access to financial services differs considerably between developing countries. According to the World Bank (2008), less than 50% of the population in most developing countries has a bank account, whereas in most Sub-Saharan African countries more than 80% of the population lacks a bank account.

The limited access to financial services by the poor is due to many reasons, such as a lack of education, a lack of collateral, and the small transactions leading to high costs for financial institutions. Since the late 1970s, however, specialized microfinance institutions serving the poor have tried to overcome these problems in innovative ways e.g. by using group-lending schemes, dynamic incentives and by

This chapter is based on Galema and Lensink (2011) hiring local loan officers. The microfinance movement has been impressive, both in terms of new programmes introduced and in terms of the number of clients that are reached. Nowadays, more than 10.000 MFIs in more than 85 countries, serve over 100 million micro entrepreneurs. Driven by increasing access to commercial funding sources, the volume of microfinance loans has risen sharply in recent years, from an estimated USD 4 billion in 2001 to approximately USD 25 billion in 2006. However, according to Dieckman (2007), the microfinance sector still faces a USD 250 billion funding gap, implying that the potential microfinance market is huge.

Currently, nongovernmental organizations serve about half of all microfinance customers, whereas commercial institutions serve less than 20 percent (Cull et al., 2009). As nongovernmental organizations receive about 40 percent of their funding from subsidies, the question arises whether nongovernmental organizations will be able to raise enough subsidies to serve the potential market. Instead, many agree that commercial microfinance, which is the for-profit part of the microfinance sector, is necessary to fund the potential untapped demand for microfinance. Indeed mainstream financial institutions e.g. commercial banks and private and institutional investors are becoming interested in the market for microfinance. Especially pension funds are willing to invest in microfinance. Still, the current proliferation of non-profit organizations and the limited profitability of the very small loans they provide to the poorest borrowers, suggest that subsidies and social investment will continue to be important (Cull et al., 2009).

In this chapter we focus on social investors, which are investors that next to financial performance also value the social performance of their investments. They have started to invest substantially in microfinance: by 2007 they have invested 4 billion dollars in microfinance (CGAP, 2008). Social investors value both the financial and the social returns of microfinance. They are willing to invest in microfinance institutions (MFIs) that are possibly less profitable and more risky, but reach poorer borrowers, i.e. have higher outreach.

One of the most controversial questions about investing in microfinance is whether there exists a trade-off between risk and return on the one hand, and outreach to the poor, on the other. Moreover, if there appears to be such a trade-off, what is the extent to which social investors are willing to accept a decrease in returns and/or an increase in riskiness in order to achieve a higher outreach. In this chapter, we add to the growing evidence that outreach and returns of MFIs are negatively correlated. Moreover, and more importantly, for the first time ever, we try to quantify the trade-off between financial returns of investing in MFIs and outreach to the poor. More specifically, the chapter aims to derive the price of increasing portfolio outreach, which investors in microfinance have to pay in terms of accepting lower returns or higher risk. The results in this chapter will help social investors to evaluate the trade-offs between financial and social returns.

In terms of the methodology we use, we assume that social investors construct a portfolio of different MFIs and we adapt the mean-variance framework of Markowitz (1958) to construct mean-variance-outreach optimal portfolios. Specifically, we incorporate outreach as an additional constraint in the portfolio optimization procedure to obtain mean-variance efficient portfolios for different degrees of outreach. This chapter proceeds as follows. Section 2 presents our data. Section 3 discusses whether there is a risk-return-outreach trade-off and supports this with some descriptive statistics. Section 4 shows how we quantify the risk-return-outreach trade-off and section 5 concludes.

4.2 Data

We use a version of the MixMarket dataset, which covers the period 1997 to 2007, to attempt to quantify the trade-off social investors face between return, risk and outreach. The MixMarket dataset is publicly available from www.mixmarket.org. All numerical data are converted to US dollars at contemporaneous exchange rates. The number of MFIs has grown explosively over the last eleven years. In 1997 there are only about 25 MFIs in our dataset, while in 2006 there are already 800 MFIs in our portfolio. MFIs can voluntarily participate in the MixMarket database, but data entry is closely monitored by MixMarket. Participants have to enclose documentation that supports the data, such as audited financial statements and annual reports.

In order to be able to provide such data, reporting MFIs should have an adequate information infrastructure. Therefore, the MixMarket database probably represents a random sample of the best managed MFIs in the world (Krauss and Walter, 2009; Gonzalez, 2007). The data reported by MixMarket are not adjusted for subsidies. These subsidies can be seen by investors as shielding a bank from bankruptcy, similar to a too-big-to-fail (TBFT) support for commercial banks (Krauss and Walter, 2008). Nonetheless, the frequency and size of subsidies is not certain and thus constitutes an investment risk. Unfortunately, we are not able to account for this risk in the present study.

4.3 The risk-return-outreach trade-off

Before turning to the analysis, we first consider to what extent there is a trade-off between return and outreach and risk and outreach. Considering the trade-off between return and outreach, it is generally agreed that it is more costly to reach poorer borrowers than it is to reach richer borrowers. Obviously, it will be more costly to administer and monitor a 1000 loans of $200 than doing the same for a single loan of $200,000. To some extent the increased costs of providing small loans can be covered by economies of scale, although after 2000 clients MFIs tend to have captured most scale benefits (Rosenberg et al., 2009). This is probably due to the labor intensive nature of microfinance in which operating expenses consist mainly of salaries, compared to fixed costs which are relatively low (Rosenberg et al., 2009). The academic literature also finds evidence of a trade-off between performance and outreach. Hermes et al. (2011) find in a stochastic frontier analysis that efficiency decreases with outreach and Cull et al. (2007) find that operating expenses decrease with average loan size

To cover the higher costs of providing small loans, MFIs set higher interest rates (Rosenberg et al., 2009). Due to these higher interest rates, also MFIs that offer relatively small loans are able to make a small profit (Cull et al. 2009). Still, the profit is modest compared to MFIs that offer larger loans. To illustrate, in our dataset the average return on assets for an average loan size below $1000 is -0.08%, while it is 1.8% for loans above $1000,-. This difference in performance of small and larger loans, which is statistically significant at 1%, implies that investing in MFIs that offer small loans is probably only of interest to social investors.

Considering the trade-off between risk and outreach, one of the main success stories of microfinance is that also very poor lenders have very high repayment rates. In addition, poor lenders typically operate in the informal sector, which tends to be less correlated to the economy as a whole (Ahlin and Lin, 2006), such that poor borrowers face less macroeconomic risk. This would imply that there is no trade-off, i.e. reaching poorer borrowers is not necessarily more risky. Investors are, however, not so much interested in borrower risk as in MFI risk, which differs among different types of MFIs. Cull et al. (2009) show that the type of organization that typically serves the richer segment of poor borrowers is different from the type of organization that serves the poorer segment. MFIs that serve the richer borrowers typically have a for-profit status, employ an individual lending method, have lower operating costs per loan, are more profitable and rely less on subsidies. By contrast, MFIs that serve the poorest borrowers typically have a non-profit status, employ a

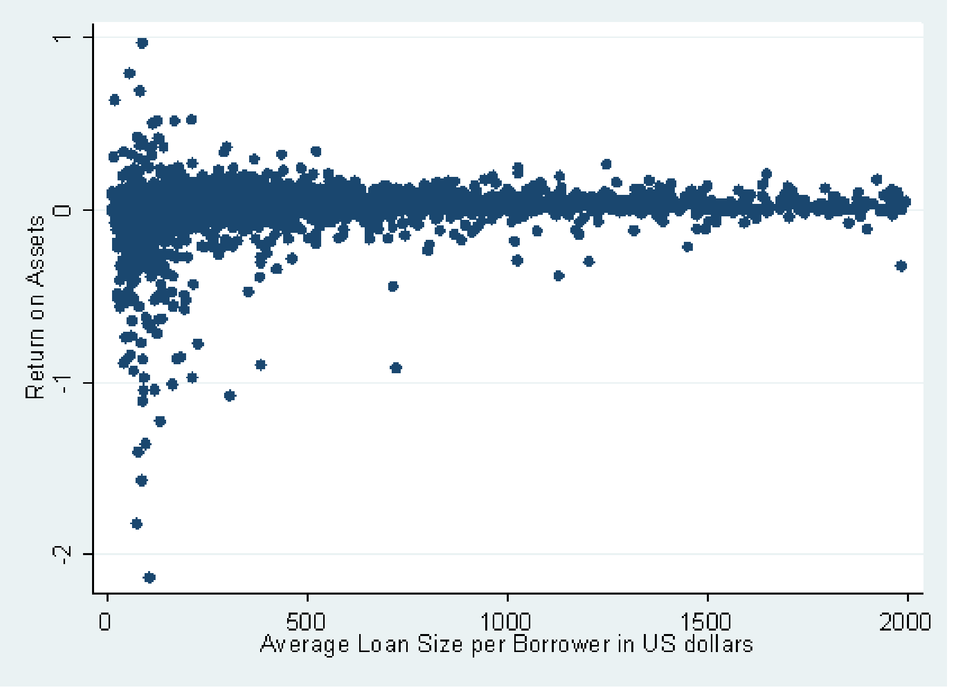

Figure 4.1. Scatter diagram of Return on Assets versus Average loan Size per Borrower

group lending method, have higher operating costs per loan, are less profitable and rely more on subsidies.

There are a number of reasons why the latter types, which are typically non-profit organizations, could be more risky. First, although they do make a profit, their after-subsidy profit depends on the amount of subsidies they receive, which creates a subsidy risk. Second, non-profit organizations are typically smaller than other MFIs: in our dataset their median amount of assets is $ 1.7 million, whereas the median amount of assets of all other MFIs is $ 3.7 million. In the advent of financial setbacks, these smaller institutions may have less deep pockets to cushion adverse shocks, like credit contraction or a system-wide decrease in repayment rates. That is, smaller institutions face higher liquidity risk. Third, non-profit organizations usually lack a broad base of deposits, such that they are more exposed to refinancing risk. In most countries MFIs need a bank status to be allowed to take deposits. Indeed, for many nongovernmental organizations that want to expand their business this is an important reason to become a regulated institution.

Figure 4.1 illustrates why MFIs that serve poorer borrowers are more risky. It shows a scatter plot of MFI return on assets versus average loan size below \$ 2000. Clearly, return on assets is much more dispersed for smaller average loan sizes, especially for average loan sizes below \$500. Consistent with Cull et al. (2009), who show that most customers are served by non-governmental organizations who serve the poorest borrowers, 2579 MFIs have an average loan size below \$1000, whereas 828 MFIs have an average loan size between \$1000 and \$2000. Although we expect that a larger group has higher dispersion, merely due to its size, also an unreported variance test shows that MFIs with an average loan size below \$1000 have significantly higher return on assets variability than those with an average loan size between \$1000 and \$2000.

4.4 Quantifying the risk-return-outreach trade-off

Now we have identified that there is a trade-off between risk, return and outreach, we are ready to quantify this trade-off. In mainstream finance, the trade-off faced by investors in terms of risk and return is usually expressed in the portfolio optimization framework of Markowitz (1958). According to this framework, investors choose optimal portfolio weights to maximize their mean portfolio return and minimize their portfolio standard deviation (from now on expected return and standard deviation, respectively). Optimal portfolios can be depicted as lying on a concave curve, the mean-variance frontier, where each point on the curve is an optimal portfolio. The mean-variance frontier can be drawn in a space with expected return on the y-axis and standard deviation on the x-axis. Portfolios on the mean-variance frontier are optimal in the sense that expected return can only be increased by also increasing risk along the frontier. That is, investors cannot obtain portfolios that lie above the frontier.

To quantify the risk-return-outreach trade-off, we adapt the Markowitz framework to include outreach. In particular, we draw a mean-variance frontier for each value of expected average loan size. We do this by constraining the portfolio optimization problem such that each portfolio on the frontier has a particular expected average loan size, which is the portfolio-weighted average of MFIs' average loan sizes. In this way we create one mean-variance frontier for each level of expected average loan size, where frontiers with a lower expected average loan size lie below those with a higher expected average loan size. By progressively lowering the expected average loan size, we try to find the price of increasing portfolio outreach, which investors pay by accepting lower returns or higher risk. A formal discussion of this methodology is presented in the Appendix.

For portfolio optimization we need relatively long time spans of data, but on Mixmarket there are only a few MFIs that report returns for a sufficient number of years. Therefore, we choose a sample of MFIs with 9 years of returns, which includes 19 MFIs over the period 1998-2006. To construct the frontiers we use return on equity, although using return on assets yields comparable results. Table 1 reports summary statistics. It shows that the majority of MFIs come from Latin America and the Caribbean and have a non-profit status. In general, non-profits appear to have lower average loan sizes and returns than banks, although there are exceptions and there is considerable heterogeneity in the sample.

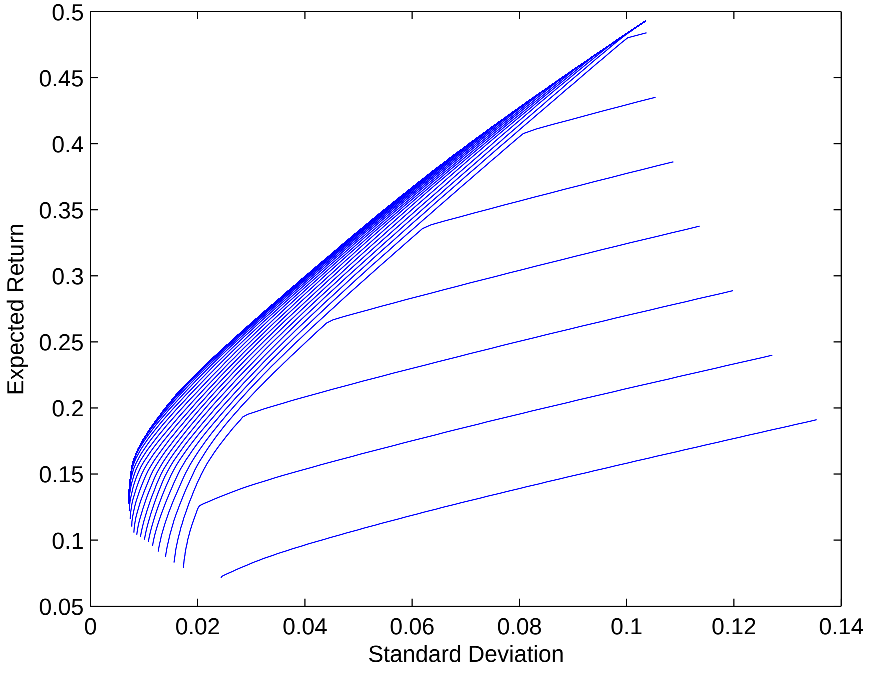

Figure 4.2. Expected return versus standard deviation

Table 4.1. Summary statistics

	MFI	Region	Type	ROA		ROE		ALS	
				mean	std.dev.	mean	std.dev.	mean	std.dev.
1	Asociacin de Consultores para el Desarrollo de la Pequea, Mediana y Microempresa	Latin America and The Caribbean	Non-profit	0.05	0.04	0.19	0.16	347.22	63.71
2	Association Al Amana for the Promotion of Micro-Enterprises Morocco	Middle East and North Africa	Non-profit	0.00	0.15	0.05	0.19	254.67	128.27
3	Association pour la Promotion et l' Appui au Dveloppement de MicroEntreprises	Africa	Non-profit	0.07	0.06	0.14	0.13	693.11	270.47
4	Banco Compartamos, S.A., Institucin de Banca Mltiple	Latin America and The Caribbean	Bank	0.26	0.12	0.49	0.10	264.00	123.35
5	BancoSol	Latin America and The Caribbean	Bank	0.02	0.01	0.14	0.10	1375.78	259.08
6	D-miro	Latin America and The Caribbean	Non-profit	0.05	0.08	0.08	0.11	334.89	183.03
7	FINCA Peru	Latin America and The Caribbean	Non-profit	0.05	0.04	0.06	0.04	143.22	18.27
8	Fondation Zakoura	Middle East and North Africa	Non-profit	0.04	0.05	0.10	0.10	138.89	53.64
9	Fondo Financiero	Latin America	Non-bank Fin.	0.02	0.02	0.11	0.09	1555.22	778.26

Table 4.1. Summary statistics, continued

	Privado PRODEM	and The Caribbean							
10	Fundacin Mundo Mujer Popayn	Latin America and The Caribbean	Non-profit	0.15	0.04	0.24	0.05	366.89	108.99
11	Fundacin WWB Colombia - Cali	Latin America and The Caribbean	Non-profit	0.06	0.04	0.17	0.12	580.22	193.80
12	Fundacin para el Apoyo a la Microempresa	Latin America and The Caribbean	Non-profit	0.08	0.03	0.14	0.05	458.89	72.90
13	Hattha Kaksekar Ltd.	East Asia and the Pacific	Non-bank Fin.	−0.01	0.06	0.01	0.10	275.33	137.68
14	KSK RPK	Eastern Europe and Central Asia	COOP	0.01	0.01	0.02	0.02	5361.44	2504.00
15	MIKROFIN Banja Luka	Eastern Europe and Central Asia	Non-bank Fin.	0.05	0.08	0.12	0.49	1524.89	656.72
16	MiBanco	Latin America and The Caribbean	Bank	0.04	0.02	0.20	0.13	902.11	377.43
17	Programas para la Mujer - Bolivia	Latin America and The Caribbean	Non-profit	0.06	0.02	0.08	0.03	147.22	20.09
18	SHARE Microfin Ltd.	South Asia	Non-bank Fin.	−0.01	0.05	0.06	0.16	83.78	14.47
19	Women's World Banking - Medelln	Latin America and The Caribbean	Non-profit	0.06	0.01	0.16	0.04	444.67	158.92

In this table we report summary statistics for the 19 MFIs in our sample. ROA indicates return on assets, ROE indicates return on equity and ALS indicates average loan size. We selected MFIs that have at least 9 years of returns and for which the covariance matrix is positive definite. The type of MFI can be Non-profit (NGO), Bank, Non-bank financial institution and COOP/Credit union (Cooperative/Credit union).

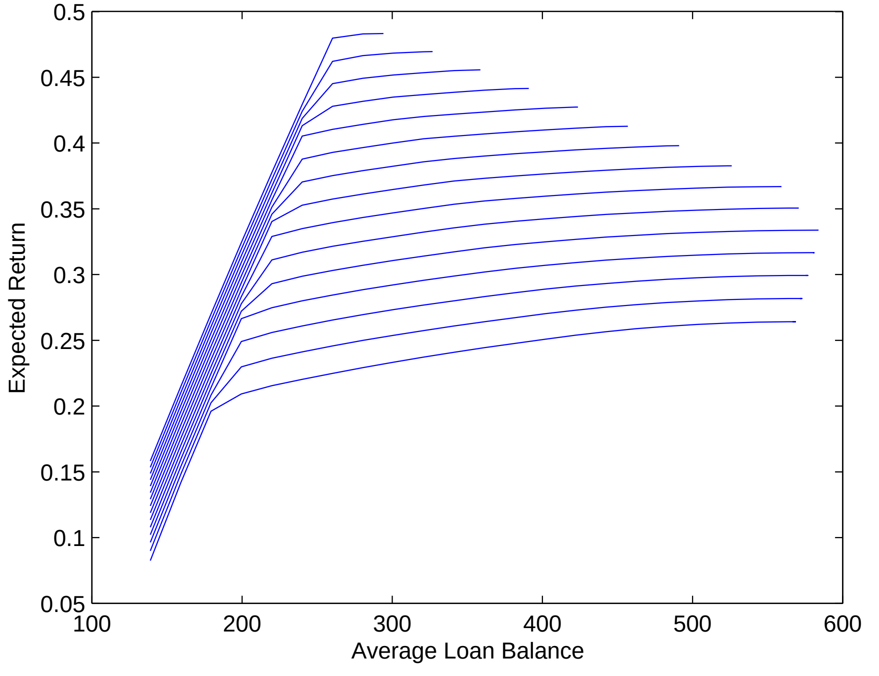

Figure 4.3. Expected return versus average loan balance

For each expected average loan size we construct a mean-variance frontier to obtain Figure 4.2. In Figure 4.2, mean-variance frontiers that have a higher expected average loan size are located above frontiers that have a lower expected average loan size. We see that for high values of expected average loan size the constraint is not very restrictive, but for lower values it becomes rapidly more restrictive. This is apparent from the fast downward shift of the mean-variance frontiers for the lower values of expected average loan size.

To quantify the trade-off between return and outreach, we plot the relationship between expected returns and expected average loan size for different standard deviations, which are vertical cross-sections of Figure 4.2. For instance, to find out how much return decreases for a standard deviation of 6.5% when we decrease expected average loan size, we can draw a vertical line at 6.5% on the x-axis, which intersects all mean-variance frontiers. At each intersection we find a value for expected return and average loans size from which we can construct a plot of expected return versus expected average loan size, i.e. a return-outreach curve. To obtain plots for multiple portfolio standard deviations, we let the standard deviation run

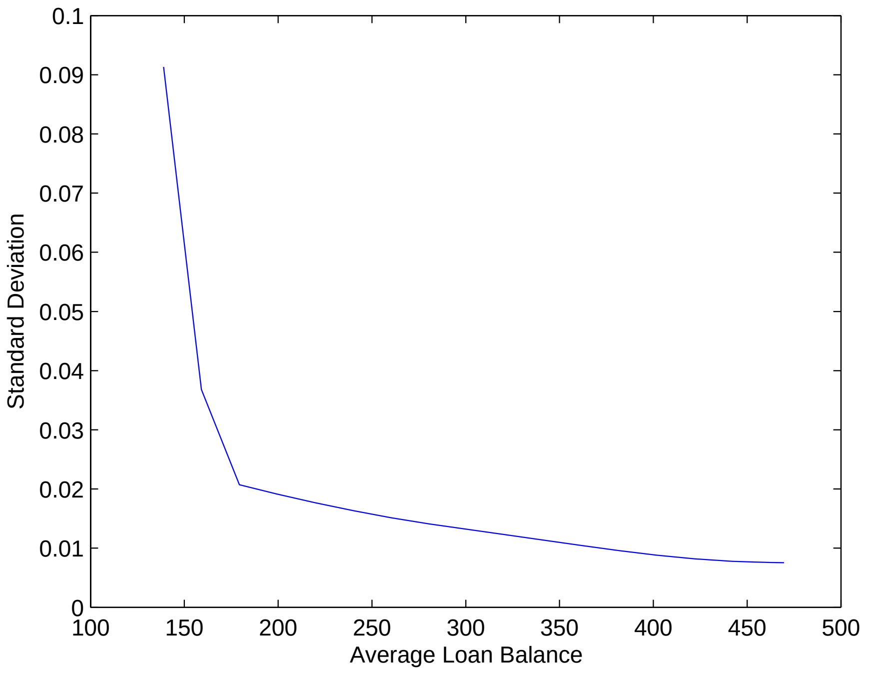

Figure 4.4. Standard deviation versus average loan balance

from 3% to 10% and take 0.5% as step size.

Figure 4.2 shows the resulting return-outreach curves. For a standard deviation of 10% we obtain the highest return-outreach curve and we obtain the lower return-outreach curves as we incrementally lower the standard deviation to 3%. The highest return-outreach curve shows the steepest drop as we lower average portfolio loan size. As we draw curves for lower standard deviations, the drop becomes less steep. So to obtain a lower expected average loan size, expected returns have to fall much more for high standard deviation portfolios than for low standard deviation portfolios. This is due to the fact that the number of assets to choose from with a certain average loan size is much smaller for high standard deviation, high return portfolios.

In Figure 4.3 and Table 4.2 we can also see that for an investor who prefers a standard deviation of 6.5%, which is the seventh curve from below, a decrease in expected average loan size from \$179.36 to \$138.89 costs 11.3% in return on equity. For the same investor, a decrease in portfolio average loan size from \$568.91 to \$179.36, will only cost about 6.8% in ROE. As shown in Table 4.2, in terms of arc

Table 4.2. The Risk-Return-Outreach Trade-Off

Average Loan Size			Expected return			Arc Elasticity (%)
Panel A: Average Loan Size - Expected Return						
Standard Deviation = 0.03						
\$138.89	→	\$179.36	0.083	→	0.196	320.80
\$179.36	→	\$568.91	0.196	→	0.264	28.30
Standard Deviation = 0.065						
\$138.89	→	\$199.59	0.124	→	0.289	222.20
\$199.59	→	\$526.12	0.289	→	0.383	31.20
Standard Deviation = 0.1						
\$138.89	→	\$240.06	0.158	→	0.430	172.90
\$240.06	→	\$294.24	0.430	→	0.483	58.10

Average Loan Size			Expected return			Arc Elasticity (%)
Panel B: Average Loan Size - Standard Deviation						
Return = 0.15						
\$138.89	→	\$179.36	0.091	→	0.021	-495.70
\$179.36	→	\$462.62	0.021	→	0.008	-104.90

This table present the risk-return-outreach trade-off. The arrows are used to indicate the increase in Average Loan Size and the corresponding change in Expected Return or Standard deviation. The Arc Elasticity indicates the average percentage change in expected return or standard deviation when we decrease Average Loan Size with one percent. This estimator of the actual elasticity, which we cannot measure since we have no functional form, is defined as: $AE_{x,y} = (x_2 - x_1)/((x_1 + x_2)/2)(y_2 - y_1)/((y_1 + y_2)/2)$, where x indicate either Expected return or standard deviation and y indicates Average Loan Size. Subscript 1 indicates the value to the left-hand side of the arrow and subscript 2 that to the right-hand size.

elasticity, a percentage decrease in outreach leads to a 320.8% increase in percentage returns in the first case, whereas a percentage increase in outreach only leads to a 28.3% increase in percentage returns in the second case. So a social investor faces a much starker trade-off between returns and average loan size for portfolios that have a lower average loan size.

Next, we quantify the trade-off between risk and outreach by taking a horizontal cross-section of Figure 4.2. That is, for an expected return of 15% we draw a horizontal line at 15% on the y-axis, which intersects all mean-variance frontiers. At each point where this line intersects a mean-variance frontier, we obtain a different standard deviation and expected average loan size. This yields a plot of the standard deviation against expected average loan size for a return of 15%, which allows us to find out how much the standard deviation increases when we decrease average loan size. We only plot the standard deviation against expected average loan size for one return level, since the range of return values that intersects all mean-variances curves is very small. Similar to our previous figures, the kink in the graph in Figure 4 shows that there is a very strong trade-off between outreach and risk for low average loan sizes. Specifically, keeping returns constant at 15%, to lower average loan size from $179.36 to $138.89 one has to accept an increase in standard deviation of 7%, which corresponds to an arc elasticity of -495.70%.

4.5 Conclusion

In this chapter we have shown that social investors in microfinance face a trade-off between, risk, returns and outreach. They face a trade-off between returns and outreach, since it is more costly to borrow to very poor borrowers. They also face a trade-off between risk and outreach, since it is typically more risky to finance the types of MFIs that serve the poorest borrowers. These types of MFIs are typically small non-profit institutions, which are more subject to subsidy, liquidity and refinancing risk than their larger for-profit counterparts. Yet, social investors are willing to accept these trade-offs, i.e. they are willing to give up some returns or to bear more risk to obtain a portfolio of MFIs that on average reduces poverty more.

To quantify how much return investors have to give up, or how much more risk they need to bear to obtain more outreach, this chapter uses the portfolio optimization framework of Markowitz (1958). We find that the trade-offs are not very large for reasonably large average loan size, i.e. average loan sizes above $180. Yet, for average loan sizes lower than $180, the trade-off is very pronounced: to lower expected average loan size from $179.36 to $ 138.89 an investor has to accept a decrease in return on equity of 11% or alternatively an increase in standard deviation of 7%.

We realize that our results are specific to our small sample and cannot be generalized to the entire population of MFIs. Also, using average loan size as a proxy for outreach is problematic in several ways. A first problem concerns outliers. An MFI can appear to have less outreach, when it has just a few very large borrowers that distort average loan size upward. Second, cross-subsidization of smaller loans with larger loans can increase total outreach. Armendáriz and Szafarz (2009) argue that in richer regions like Latin America, there is actually more scope for cross-subsidization, which implies that the higher average loan size observed in this country are not necessarily a sign of mission drift. Third, comparing average loan size across countries is problematic since different countries are in different stages of development, such that a large loan in one country can be a small loan in another.

Nevertheless, we believe that the approach presented in this chapter clearly illustrates the trade-offs between financial and social returns of investing in microfinance. While additional research has to be done, and much more data collection is needed before any solid conclusion can be reached, we hope that the techniques presented in this chapter will be valuable for microfinance investors to evaluate the trade-offs between financial and social returns.

4.A Methodology appendix

We assess the effect of constraining the mean-variance optimization for different degrees of outreach. We plot the mean-variance frontier by solving the following quadratic program for 100 different expected portfolio returns, $E[R]$:

$$\begin{aligned} \min_{\mathbf{x}} \ & \mathbf{x}'\mathbf{\Omega}\mathbf{x} \\ \text{s.t.} \quad & \mathbf{x}'\bar{\mathbf{r}} = E[R]_j \qquad j = 1, ..., 100 \\ & \mathbf{x}'\boldsymbol{\iota} = 1 \\ & \mathbf{x} \geq \mathbf{0} \end{aligned} \tag{4.A.1}$$

where $\mathbf{x}$ is a vector of weights, $\mathbf{\Omega}$ is the variance-covariance matrix of returns, $\bar{\mathbf{r}}$ is vector of expected returns of the assets included in the optimization and $\boldsymbol{\iota}$ indicates a vector of ones.

We can further constrain this optimization by demanding that the optimal portfolio's average loan balance should be smaller than some pre-specified amount of the expected average loan size, $E[ALS]$. The lower $E[ALS]$ is, the more constrained the optimization is. In this way we can plot a mean-variance frontier for each $E[ALS]$ by solving the following quadratic program:

$$\begin{aligned} \min_{\mathbf{x}} \ & \mathbf{x}'\mathbf{\Omega}\mathbf{x} \\ \text{s.t.} \quad & \mathbf{x}'\bar{\mathbf{r}} = E[R]_j \qquad j = 1, ..., 100 \\ & \mathbf{x}'\boldsymbol{\iota} = 1 \\ & \mathbf{x} \geq \mathbf{0} \\ & \mathbf{x}'\overline{\mathbf{ALS}} \leq E[ALS] \qquad E[ALS] = \min(\overline{\mathbf{ALS2}}), ..., \max(\overline{\mathbf{ALS2}}) \end{aligned} \tag{4.A.2}$$

where $\overline{\mathbf{ALS}\}}$ is a vector with expected ALS's of the assets and $\overline{\mathbf{ALS2}}$ is the same vector only with the maximum and minimum value excluded.[1] Obviously, frontiers plotted for higher values of $E[ALS]$ will lie above frontiers plotted for lower values of ALS.

[1] Note that we do this to prevent portfolio formations based on one asset